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Design And Implementation Of Predictive Compressed Sensing Algorithm for Environmental Data Compression In Wireless Sensor Network

R. K. Shaiksha Moula[1], Shaik Ishaq Anwar[2] , Mohammed Shahid Nawaz[3], Dr. Parnasree Chakraborty[4]

[1]*Dept of Electronics and Communication,*
BS Abdur Rahman Crescent Institute of Science & Technology
Chennai,India
[2]*Dept of Electronics and Communication*
BS Abdur Rahman Crescent Institute of Science & Technology
Chennai,India
[3]*Dept of Electronics and Communication*
BS Abdur Rahman Crescent Institute of Science & Technology
Chennai,India
[4]*Dept of Electronics and Communication*
BS Abdur Rahman Crescent Institute of Science & Technology
Chennai,India

Abstract—

Wireless sensor networks (WSNs) are highly resource constrained in terms of power supply, memory capacity, communication bandwidth, and processor performance. Compression of sampling, sensor data, and communications can significantly improve the efficiency of utilization of three of these resources, namely, power supply, memory and bandwidth. Recently, there have been a large number of proposals describing compression algorithms for WSNs, The main objective of this paper is to compress the environmental data which can be predictable for given data sample.In this paper we are going to use CS algorithm/Lossy compression that works in its maximum efficiency when the nature of data is sparse and hence to generate sparsed data a prediction filter is used.Reconstruction of data will be performed at the decoder.Implementation using NI-WSN module will be done

Keywords—Wireless sensor networks, compression

I. Introduction

Wireless sensor networks (WSNs) are critically resource constrained by limited power supply, memory, processing performance, and communication bandwidth [Akyildiz et al. 2002]. Due to their limited power supply, energy consumption is a key issue in the design of protocols and algorithms for WSNs. Typically, energy consumption is dominated by radio communication [Pottie and Kaiser 2000;

Barr and Asanovic].The energy consumption of radio communication is directly proportional to the number of bits of data, that is, data traffic, transmitted within the network. Therefore, using compression to reduce the number of bits to be transmitted has the potential to drastically reduce communication energy costs and so increase network lifetime. Similarly, sampling-level [Candes and Wakin 2008; Haupt et al. 2008] ` and communication-level [Lu et al. 2010; Tulone and Madden 2006] compression can reduce energy costs in WSNs and increase network lifetime. In most cases, the savings due to compression are greater than linear, since reducing the number of bits transmitted has the knock-on effect of reducing link-level congestion, which in turns reduces the number of collisions and re-tries in the network. Consequently, researchers have been investigating optimal algorithms for compression of sensed data, sampling, and communications in WSNs. Unfortunately, most conventional compression algorithms are not directly applicable to WSNs. First, in conventional compression approaches, the key objective is to save storage, not energy. In WSNs, energy is more important than memory. Thus, energy saving is the primary evaluation metric. Second, it has been shown [Sadler and Martonosi 2006] that, in terms of energy consumption, transmission of just one byte of data is equivalent to execution of roughly four thousand (Chipcon CC2420) to two million (MaxStreamXTend) instructions. These calculations only consider local energy consumption at the compressing node; network-wide energy savings due to compression can further compensate for the energy expense of compression. Thus, compression algorithms with some degree (low or medium) of computational complexity are worth exploring. On the other hand, excessively computationally complex algorithms are not worth pursuing. Finally, conventional compression algorithms, originally designed for desktops or servers, must be restructured to reduce code size and dynamic memory usage due to the limited memory capacity of WSN nodes—typically less than 50 kB for code memory and even less for data memory. Recently, researchers have addressed these challenges by adapting conventional compression techniques and, in some cases, by proposing new approaches002E

I. LITRERAUTRE REVIEW

The observation of researchers in recent years has deployed for the utilization of data aggregation methods on basis CS for enhancing the lifetime of network for the reduction of data transmission and traffic balance across the entire sensor network.

Feizi et al., [10] shown as the scheme of data transmission, firstly it can use sensing compression for data compression, it can be applied and simulated for the coding of network. Since these two methods are not dependent among themselves, this cannot be utilized fully for the combination of two algorithms and its characteristics which can further enhance signal processing and its efficiency respectively.

Luo C. et al in [11] determines the compression of sensing in multi-hop wireless sensor network for data collection in large-scale. The reduction of traffic in the network can be more effective and the load balancing can be maintained which can prolong the execution time of the network in this method. This author also addresses the random projection which is dense will not show execution enhancement of the networks that also furnishes the strategy for data collection of sensing in hybrid compression.

Vuranet al.[12] indicated in sensor networks, the addressed circumstances have high spatial and correlated temporally by sensors. The sparsity of sensor can results in these correlations with the sensor readings also with the wavelet transform with sparse requirements to satisfy the CS theory.

In [13] the authors address the framework of Compressive Data Gathering (CDG) to utilize the intersignals of sparsity in fashion of multi-hop in wide dense in the sensor

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networks. Matrix Completion (MC) is used to reconstruct full data matrix from part of its entries. In recent developments, E. J. candès et al. proves that this approach can recover missing entries from an incomplete set of entries, when the data matrix is at lower rank or at low rank matrix approximately.

Wang et al., in [14] indicates the scheme of energy efficiency: the random vector of sparse has been generated by each node. The adding up of vector from previous node(s) can result in next hop node for forwarding. The total number of communications by generating Sparse Random Projections (SRP) has been reduces by this scheme. Although, the frequent changes of routing paths leads to SRP, which are difficult to achieve in wireless sensor networks.

II. PROPOSED OBJECTIVE

- In the proposed system, we are using compressive sensing(CS) algorithm/Lossy compression which reduces the size of the data.
- The CS shows that sparse signals and information in WSNs can be exactly reconstructed from a small number of random linear measurements.
- This project provides most recent survey of CS theory as it is applied in WSN.
- Here few environmental data samples are considered, found MSE and Autocorrelation for each data set.
- The data sets which are giving the autocorrelation ranges from 0.2 to 0.9 and MSE <0.5 are used for prediction purpose.
- The data sets which are giving better results, should be given to CS algorithm such that it reduces the size of the data.

III. COMPRESSED SENSING

Three inherent inefficiencies of transform coding motivate the need for alternative compression techniques: First, compressing high-dimensional signal means processing a large number of samples n. Second, the encoder must compute all transform coefficients θ(n), even though it will discard all but K(n K) of them. Finally, the encoder must encode the indices of large coefficients. This increases the coding rate, since these indices change with each signal. In this context, compressed sensing (CS) has been proposed as This section describes the high level architecture for the smart parking system along with a mathematical model. The parking system that we propose comprises of various actors that work in sync with one another. Below is the mathematical model that defines our smart parking system.
a potential alternative, since the number of samples required (i.e., proposed number of sensors that need to transmit data), depends on the characteristics (sparseness) of the signal [Donoho 2006, Candes et al. 2006, Candes and Romberg 2007].

Sparsity arises in WSN data due to spatiotemporal correlations within the sensor readings. The asymmetric computational nature of CS also makes it attractive for WSN data compression. In CS, most computation takes place at the decoder (sink), rather than at the encoder (sensors), thus sensors with minimal computational performance can efficiently encode data. The CS field (also known as compressive sampling) field has existed for at least four decades, but recently (about 2004) researchers' interest in the field has exploded due to several important results obtained by Donoho [2005, 2006] and Candes et al. [2006]. CS is a novel sensing/sampling paradigm that goes against the traditional understanding of data acquisition. These works on CS milestone showed that if a signal has a sparse representation in one basis, then it can be recovered

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from a small number of projections onto a second basis, which is incoherent with the first one.

A prerequisite for CS is a tractable recovery procedure that can provide exact recovery of a signal of length n and sparsity K. In other words, a signal can be written as a sum of K basis functions from some known basis, where n K. CS is promising for many applications, especially in sensing signals that have a sparse representation in some basis. Rather than sampling a K-sparse signal n times, only M = O(Klogn) incoherent measurements are sufficient. Moreover, at the encoder, no manipulation is required for the M measurements except, possibly, some quantization. For more advanced and detailed information on CS theory, readers are referred to Candes and Wakin [2008], ` Haupt et al. [2008], and Balouchestani et al. [2011] and references therein.

- X=[x1 x2 ……xN] of matrix order 1*N
- Y=[y1 y2 ……yM] of matrix order 1*M

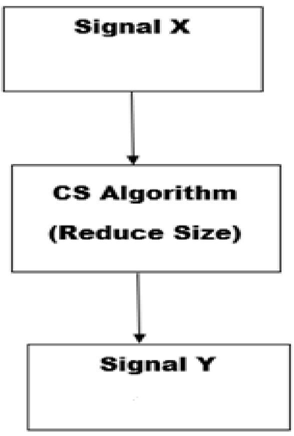


Fig.1 Flowchart of CS Algorithm

- Newsampling theory that leverages compressibility.

  y= ϕ s (1)

  y-reduced set of signal(x).

  ϕ -measurement matrix(ϕ 1, ϕ 2,…. Φm).

  s-sparse signal which is given as

  s= Ψ.x(2)

  Therefore,

  From (1) and (2), y= ϕ (Ψ.x)

  = [A].[x]

  =[y]

  A is CS Matrix.

In the technique of Lossy compression, it decreases the bits by recognizing the not required information and by eliminating it.[3]The system of decreasing the size of the file of data is commonly termed as the data-compression, though its formal name is the source-coding that is coding get done at source of data before it gets stored or sent[4]. In these methods few loss of the information is acceptable. Dropping non-essential information from the source of data can save the storage area. The Lossy data-compression methods are aware by the researches on how the people anticipate data in the question. As an example, the humaneye is very sensitive to slight variations in the luminance as compare that there are so many variations in the color. The Lossy image compression technique is used in the digital cameras, to raise the storage ability with the minimal decline of the quality of picture. Similarly in theDVDs which uses the lossy MPEG-2 Video codec technique for the compression of the video. In the lossy audiocompression, the techniques ofpsychoacoustics have been used to eliminate the non-audible or less audible components of signal.

Data Sets(Samples) for M=100	Auto Correlation
pH of soil	0.0677
Di-Urnal Temperature	0.0254
Sea Temperature	0.892
Total Organic Carbon	0.2977

Table-1 Data sets Sample(1200)

IV. IMPLEMENTATION & WORKING

In the Encoder part,first we have given 250 samples of data(x) to prediction filter(Auto Regression Model),this AR model will predict the values upto 1200(x')(according to algorithm used in code).Now, the error values(e) will be calculated by subtracting the predicted values from the original data set. These error(e) values will be given to CS algorithm which reduces the size of the data (e') (upto 100).These error values(e') which are obtained from CS algorithm will be transmitted to receiver part i.e to CS reconstruction which will give the original error values(e). And this original error values will be given to prediction part which produce the original data(x).

Data Compression ratio=US/CS

US-Uncompressed size of data.

CS-Compressed size of data.

In this project, Uncompressed size is 1200 and compressed size is 100.

Therefore, Compression ratio=1200/100

=12/1(read as 12 to 1)

Space Savings = (1 - CS/US)×100

= (1 – 100/1200)×100

=91.67%

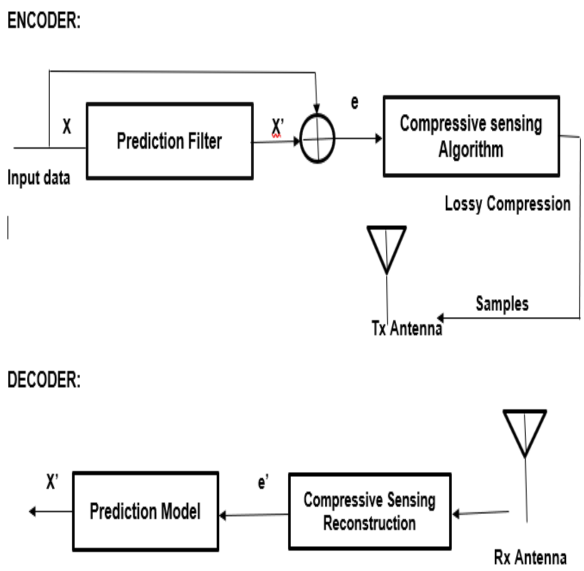
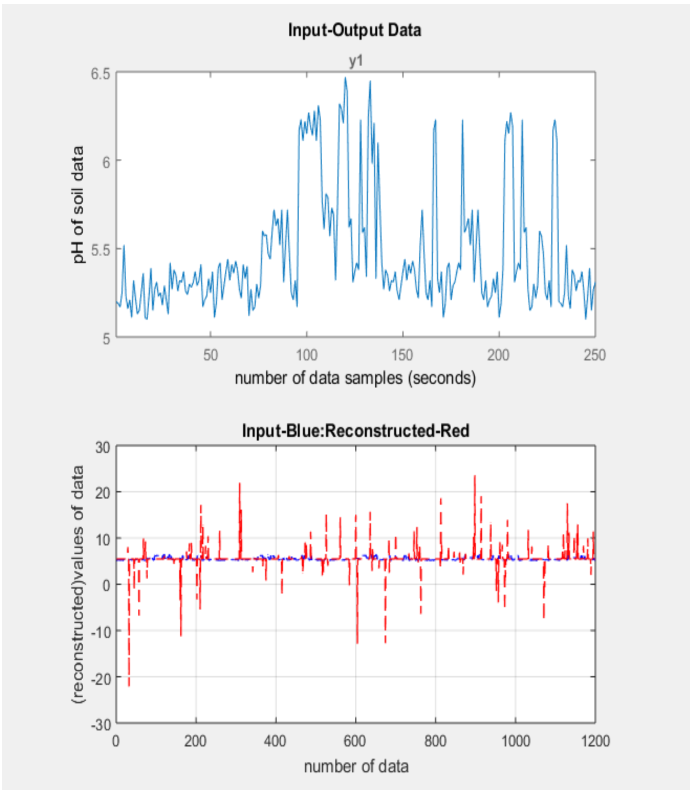


Fig.2 Block Diagram of the System

Fig.3.Temperature Wave Form

DATA SET-ORIGINAL AND RECONSTRUCTION SIGNAL:



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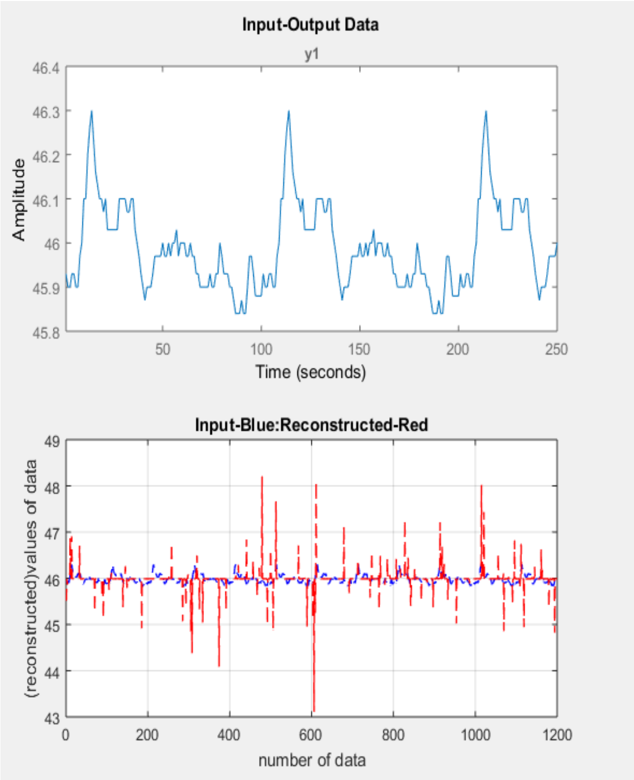

Fig.4 pH of soil

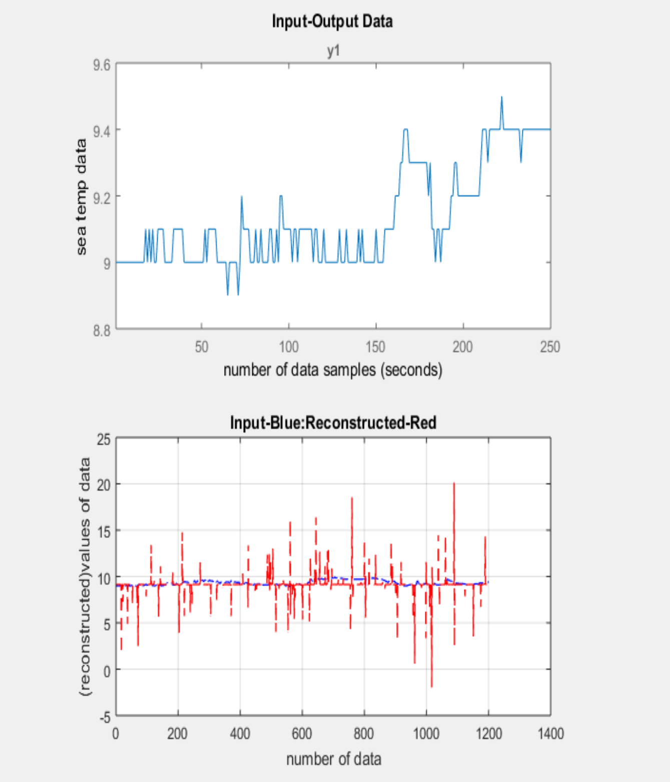

Fig.6 Sea Temperature

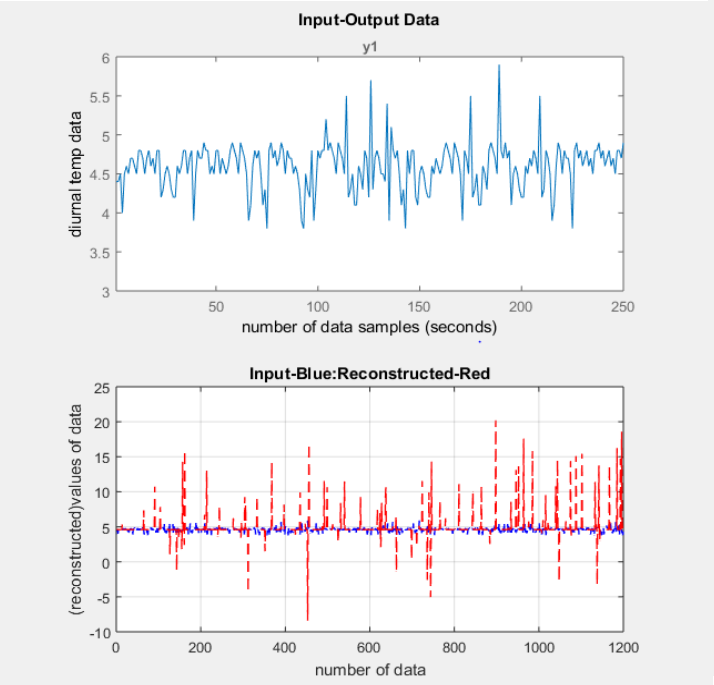

Fig.5 DiurnalTemperature

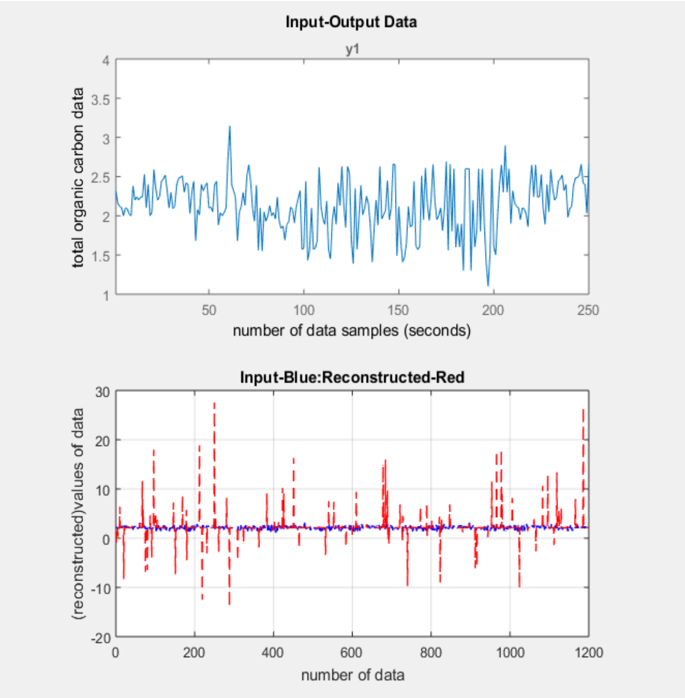

Fig.7 Total Organic Carbon

V. CONCLUSION

With the emergence of new technologies such as IoT where heterogeneous networking architectures need to be integrated to perform a variety of tasks, handling and integration of a large amount of data generated by the interaction of multiple factors/sensors keeps continuously challenging. In particular, future WSNs are expected to integrate with a variety of other networks such as wireless mesh networks, Wi-Fi, and vehicular networks to make smart platforms for IoT applications.

Understanding the role of CS, as a tool to cope with the problem of data deluge, is of great importance in making such applications realizable.

A Scalable Network Processing Exploiting Sparsity in Multiple Dimensions with Heterogeneous Data As discussed in Section III, in CS based data gathering, the attention is mainly given to the case when sparsity is defined with respect to a single vector; temporal as in III-A and spatial as in III-B. To exploit spatio-temporal correlation in data gathering, there are a few approaches as discussed in Section III-C which define sparsity in 2-dimensions (2-D). Mainly, the ideas of Kronecker CS and matrix completion [14], [18] have been exploited under restricted assumptions such as centralized processing. Further, when exploiting Kronecker CS ideas, reconstruction is performed after transforming 2- D (spatio-temporal) data to a single vector which requires large memory and computational costs. Such requirements are not desirable especially with on-line WSN applications.

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